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Improved Genetic Algorithms by Means of Fuzzy Crossover Operators for Revenue Management in Airlines

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Abstract: Revenue Management is an economic policy that increases the earned profit by adjusting the service demand and inventory. Revenue Management in airlines correlates with inventory control and price levels in different fare classes. We focus on pricing and seat allocation problems in airlines by introducing a constrained optimization problem in Binary Integer Programming (BIP) formulation. Two BIP problems are represented. Moreover, some improved Genetic Algorithms (GAs) approaches are used to solve these problems. We introduce new crossover operators that assign a Fuzzy Membership Function to each parent in GAs. We achieve better outputs with new methods that take lower calculation times and earn higher profits. Three different test problems in different scales are selected to evaluate the effectiveness of each algorithm. This paper defines new crossover operators that help to reach better solutions that take lower calculation times and more earned profits.

Key words: Genetic Algorithms (Gas) · Operational Research (OR) · Binary Integer Programming · Revenue Management · Fuzzy Logic

INTRODUCTION

Air Transportation has been faced a continuous growth in number of airlines passengers, in recent years. The Federal Aviation Administration (FAA) predicts that this demand will increase even with higher rates in future.

Large airline companies may have approximately 3000 daily flights. If the revenue from each flight could be increased by only 100$, this would result in an annual revenue increase of 109,500,000$. This simple example emphasizes revenue management potential to achieve high revenue [1].

Revenue management is a business principle that balances supply and demand to control price and/or inventory availability in order to maximize revenue and profit growth. In other words, Revenue Management is the allocation of limited resources between some customers. It uses to make higher profits with a particular investment in capacity. The impact of revenue management is most significant in business environments where the following conditions exist:

Inventory is perishable; Supply is fixed or can not be adjusted in the short run; Demand can be segmented based on a number of marketing factors; Demand is stochastic; Inventory can be sold in advance.

Service industries, particularly those in the travel and transportation markets, often satisfy all or most of these conditions. Although its impact depends on the size of the company and the complexity of its operations, an estimate of 2 -10% in revenue increase has been directly attributed with revenue management [2,3].

Revenue management has also taken hold widely throughout the rest of the Travel industry as well. Almost all major Hotels, Car Rental Agencies, Cruise Lines and Passenger Railroad firms have revenue management systems [4].

Revenue or Yield Management techniques are comprised of some basic parts that are grouped in 3 basic categories: Product Design, Pricing and Capacity Allocation. These parts are in a completely close relation with each other.

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In Air Transportation, travel programs (passengers' routes from source to their final destinations include one or more non-stop flight at a specific departure time) determine the inventory or seat allocation capacity and airline customers demonstrate the demand.

The total passenger demand for each travel program and combination of fare classes is assumed to be a stochastic process. It is represented by an Exponential distribution function. Exponential function is a useful density function to estimate the distances between arrival times of "customers" to a system if it has a fixed rate, as followed:

$$f(x) = \begin{cases} \frac{1}{\beta} e^{-\frac{x}{\beta}} & if \quad x \geq 0 \\ 0 & otherwise \end{cases} \tag{1}$$

$$F(x) = \begin{cases} 1 - e^{-\frac{x}{\beta}} & if \quad x \geq 0 \\ 0 & otherwise \end{cases}, \beta > 0 \tag{2}$$

That β is Mean and Scale parameter for this density function [5,6].

Therefore, the number of allocated seats for a fare class in a travel program is determined with exponential density function $f(x)$.

$f(x)$ is the corresponding cumulative distribution function, too. In other words, is the probability of increasing passengers to a specific digit in a fare class for a travel program. Cumulative distribution function will be used to define Maximum Predicted Revenue (α_{ijk}) in section 2.

It is to be noted that using exponential distribution is not a principal assumption in this article and could be replaced by other proper distribution functions such as Normal, Gamma and the other ones.

In addition, price structure and seat allocation policies must be formulated in consistency with constraints imposed by the airlines computer reservation system (CRS) such as level-of-service (nonstop, direct, single-connect, or double-connect), connection quality variables, carrier, carrier market presence, fares, aircraft size and type variables and time of day among others, which limits the number of fare classes [7,8].

Some of the major CRSs are Apollo, EAASY SABRE and System One.

A joint seat allocation and fare-pricing competition model for stochastic demand is proposed in [9]. A numerical analysis is presented to demonstrate the impacts of various market conditions on the payoffs, booking limits and pricing strategies of the competing airlines. A multistage stochastic programming approach to airline network revenue management is presented in [10]. The objective is to determine seat protection levels for all itineraries, fare classes, points of sale of the airline network and all booking horizons such that the expected revenue is maximized. [11] represents a semi-Markov Decision Problem that considers a single flight-leg with multiple fare classes, overbooking of the flight, concurrent demand arrivals of passengers from the different fare classes and class-dependent, random cancellations. This problem is solved with a stochastic optimization technique. In [12], maximum number of average fare data is selected and this problem is formulated using Binary Integer Programming. [13] combines a stochastic gradient algorithm and approximate dynamic programming ideas to improve important issues like demand uncertainty, nesting and the dynamic nature of the booking process. [14] outlines a Revenue Management approach suited to the pricing policy of low-cost airlines, where each flight only has one fare available at any point of time. Effective Revenue Management boils down to a flight-by-flight dynamic price optimization.

The remainder of this article is developed as follow: section 2 represents some basic assumptions and mathematical formulations in order to apply revenue management to airlines in the Binary Integer Programming formulations. Section 3 introduces some methodologies that are used to solve BIP problems. In section 4, Computational Results and some comparisons between different kinds of crossover operators have been mentioned. Finally, section 5 is prepared as conclusion of the paper.

Basic Assumptions and Problem Formulation: A wide variety of problems can be represented as discrete optimization models. An important area of application concerns the efficient management of a limited number of resources to increase productivity and/or profit. Such applications are encountered in Operational Research problems such as goods distribution, production scheduling and machine sequencing [15].

We propose two versions of Pricing and Seat allocation model in the BIP formulation in this paper due to [16].

The following are the basic variants introducing the Pricing & Fleet seat allocation system:

- Flight Leg Capacity (A_l) is the assigned aircraft capacity of a flight leg.
- The similar combinations of fare classes that are considered as each flight leg represent selected fare classes in CRS (CRS Capacity (M)).
- Travel Programs include one or more flight legs that should be considered for customers.
- Maximum Predicted Revenue(α_{ijk}) is estimated for each seat as:

$$\alpha_{ijk} = T_{ik} \times P(j_{ik}) \tag{3}$$

Where T_{ik} is the price for *i-th* travel program and fare class k and $P(j_{ik})$ is the probability of increasing passengers from (j-1) seat in travel program i and fare class k [6].

$X_{ijk}$is binary decision variable for travel program i, *j-th* seat and fare class k,W_{im} is binary decision variable for travel program i and price structure m. Also, $\Lambda(i)$ describes the similar combinations of price structures for travel program i,$\pi_i$represents seat allocation capacity for travel program i,$I(l)$shows travel programs that contain *l-th* flight leg and K(i) is a set that includes all of fare classes selected for travel program i.

It is notable that $\Gamma(im)$ is a set of fare classes that does not exist in travel program i and price structure m.

In continuation to this section, two different models of the combined Pricing & Seat allocation problems are described.

Problem1: With aggregate the basic model that is represented in [16] over all seats of the travel program i (in constraints (7)), we have this formulation:

$$Z(x) = Maximize \sum_{i \in I(l)} \sum_{j=1}^{\pi_i} \sum_{k \in K(i)} \alpha_{ijk} X_{ijk} \tag{4}$$

Subject to

$$\sum_{i \in I(l)} \sum_{j=1}^{\pi_i} \sum_{k \in K(i)} X_{ijk} \le A_l \quad \forall l \in L \tag{5}$$

$$\sum_{m=1}^{\Lambda(i)} W_{im} = 1 \quad \forall i \in I \tag{6}$$

$$\sum_{j=1}^{\pi_i} X_{ijk} + W_{im} \le 1 \quad \forall i \in I; m = 1,\ldots,\Lambda(i); k \in \Gamma(im) \tag{7}$$

$$X_{ijk} \,\&\, W_{im} \in \{0,1\} \quad \forall i \in I; j = 1,\ldots,\pi_i; k \in K(i); m = 1,\ldots,\Lambda(i) \tag{8}$$

The objective function (4) maximizes the predicted revenue for all seats of travel programs in the considered fare classes. Constraints (5) establish that the total number of assigned passengers can not exceed the aircraft capacity of a fight leg. Constraints (6) assure that only one price structure is selected for each travel program. Also, Constraints (7) insure that fare classes should select from the defined price structure of each travel program. Finally, constraints (8) determine that all decision variables should be binary.

Problem 2: With aggregation of basic model over all seats of travel program i and fare classes that does not exist in price structure m:

$$\sum_{j=1}^{\pi_i} \sum_{k \in \Gamma(im)} X_{ijk} + \pi_i \times |\Gamma(im)| \times W_{im} \le \pi_i \times |\Gamma(im)| \quad \forall i \in I; m = 1,\ldots,\Lambda(i) \tag{9}$$

The second problem is developed by replacing (7) with (9) (see [6]).

Notice that Problem1 has one and Problem2 has two independent aggregations.

The optimal solutions in represented BIP problems are the highest profit that an airline can reach to it. However, an airline usually can not calculate the optimal solution in large-scale companies and then, they should satisfy with only sub-optimal solutions. Closer solution to optimal, more profit.

Another parameter that is too important for an airline is the required calculation time to providing a solution.

This paper define new crossover operators that help in order to reach better solutions with lower calculation times and more profits. In other words, these heuristic algorithms help us to apply more accurate and quicker management in airlines.

Solution Methodology: Computational complexity of Integer programming problems depends on three basic factors:

- Number of integer variables
- Problem structure
- The linear constraints of the problem

It is notable that sometimes when the number of integer programming constraints is increased, computational complexity is fallen, due to significant decrease in the number of feasible solutions.

The number of solutions in the integer programming problems with n binary variables is 2^n. However, the number of solutions would be reduplicated when one variable is added. As a result, the completeness of these problems will grow exponentially.

Branch-and-Bound, Cutting Planes, Branch-and-Cut and Branch-and-Price are some of the most conventional classic techniques used in solving BIP problems. These methods have returned acceptable results for these problems in fairly small-scale cases. However, the solution procedure in large-scale problems faces many difficulties i.e. optimal solution is not achieved and/or it takes long times to reach optimal results.
Therefore, newer computational procedures are needed to overcome these mentioned deficiencies. In this way, researchers have tended to stochastic optimization methods such as evolutionary and Swarm Intelligence algorithms. They respectively model natural evolution and social behaviors in the form of algorithmic mechanisms.

These methods review works done on previous steps, implement search procedure and attempt to improve solutions in execution process.

Genetic Algorithms, Evolution Strategies, Particle Swarm Optimization are the most conventional instances of them.

Gas are heuristic methods that help to find better solutions in NP-complete problems. They use some strings of symbols called chromosomes. Solutions are represented on these strings directly or with using a defined transformation function.

Selection, crossover and mutation are the main operators of the genetic search. The repeated use of these operators is a filtering process, which results in the subsequent populations of individuals with better fitness values. This probabilistic nature of GA makes it a unique algorithm for convergency towards the global optimum. However, being a heuristic search method, GA can not guarantee finding the optimal solution [17].

Since GAs are usually used in NP-complete problems, the distance between returned solution and the optimal solution is unknown.

To find more complete information about GAs, refer to [18].

Gas are being applied to a great number of integer programming problems in practical cases such as Vehicle Routing Problems (VRP), Traveling Salesman Problems (TSP), Production Planning Problems in Flexible Manufacturing Systems (FMS), Transportation Logistics Problems, Path & Trajectory Planning for robots and 0-1 Knapsack Problems [12].

Also, these algorithms have remarkable potential to improve solution methods due to their flexibility and robustness in execution process.

Improving the crossover operation is the main contribution of this article. In continuance, some new heuristic crossover operators are introduced. These operators assign Fuzzy Membership Function to each parent. These functions are allocated to parents chromosomes. Then, they are combined according to their membership functions.

Crossover Operators for Genetic Algorithms

Fuzzy-Arithmetic Weighted Mean (FAWM) (Bell Shape Type1): This operator returns children that are fuzzy-arithmetic weighted mean of two parents [20]. In the crossover procedure, algorithm considers cost function and allocates respectively a fuzzy membership function to each parent due to their fitness function values. After that, intersection point values of each membership function with the fittest parent one (the elite chromosome) are estimated as weights.

These coefficients (weights) determine children as FAWM of two parents, as below:

$$P_{(i+1)j} = \omega_{B_{ij}} \times P_{ij} + (1-\omega_{B_{ij}}) \times P_{i(j+1)} \qquad (10)$$

In above equation, P represents generated parents in crossover process. Its first entry is the Generation number and the second one is the parent number in Genetic Algorithm. $\omega_{B_{ij}}$ is the weight allocated to *j-th* parent that is returned in *i-th* iteration.

In this crossover operation, Bell shape membership functions are selected (Figure 1).

It is noted that all generated children in above process are feasible with respect to linear constraints of the optimization problem.

Fuzzy-arithmetic Weighted Mean (Bell Shape Type2): This type is the same as previous one except that the fittest parent in each generation (P_{i1}) is selected as a common parent of next generation children. The other parents ($P_{i(j+1)}$) play the role of second parents, respectively.

$$P_{(i+1)j} = \omega_{B_{ij}} \times P_{i1} + (1-\omega_{B_{ij}}) \times P_{i(j+1)} \qquad (11)$$

In Table 1, Bell shape functions are used to calculate the Fuzzy-Arithmetic Weighted Mean in numerical examples:

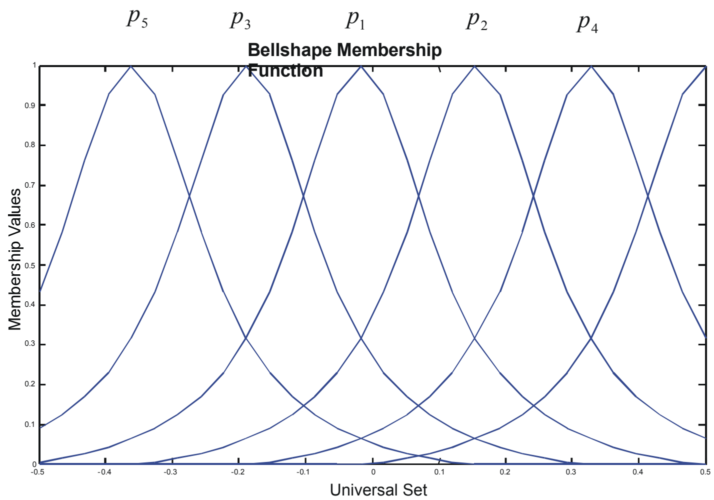

Fig. 1: Bell shape fuzzy membership functions and their intersection points

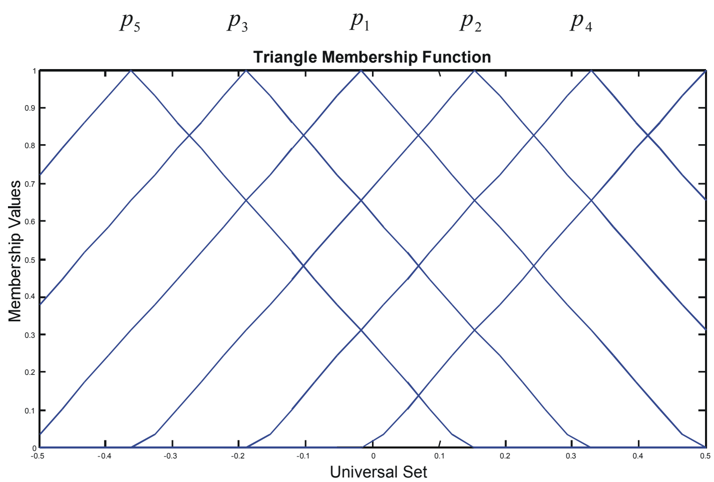

Fig. 2: Triangular shape fuzzy membership functions and their intersection points

Fuzzy-Arithmetic Weighted Mean (Triangular Shape Type 1): This methodology is implemented similar to the first operator (section 3.1.1) but only membership functions that are allocated to parents are in triangular shapes (Figure 2).

Equation (13) determines the FAWM crossover that is used triangular functions.

$$P_{(i+1)j} = \omega_{T_{ij}} \times P_{ij} + (1-\omega_{T_{ij}}) \times P_{i(j+1)} \tag{12}$$

In above formula, $\omega_{T_{ij}}$ is the assigned weight for *j-th* parent in *i-th* rung.

Fuzzy-Arithmetic Weighted Mean (Triangular Shape Type 2): Finally, this method is runed in the similar way with section 3.1.2 but only triangular functions are selected for parents:

Table 1: Bell shape membership functions in fawm crossover

Pi	Wi	P' i+1	P"i+1
Pi1=10	Wi1=1	P'(i+1)1=10	P"(i+1)1=10
Pi2=20	Wi2=0.68	P'(i+1)2=23	P"(i+1)2=16
Pi3=30	Wi3=0.67	P'(i+1)3=33	P"(i+1)3=20
Pi4=40	Wi4=0.33	P'(i+1)4=47	P"(i+1)4=37
Pi5=50	Wi5=0.32	P'(i+1)5=57	P"(i+1)5=44

Notes

Pi: generated parents in *i-th* iteration

P' i+1: generated parents in *(i+1)-th* iteration by using Bell shape Functions (Type 1)

P"i+1: generated parents in *(i+1)-th* iteration by using Bell shape Functions (Type 2)

Pi, P' i+1, P"i+1 are rounded decimal values equal with chromosomes' binary strings.

Table 2: Triangular shape membership functions in fawm crossover

Pi	Wi	P' i+1	P''i+1
Pi1=10	Wi1=1	P'(i+1)1=10	P''(i+1)1=10
Pi2=20	Wi2=0.8	P'(i+1)2=22	P''(i+1)2=14
Pi3=30	Wi3=0.8	P'(i+1)3=32	P''(i+1)3=16
Pi4=40	Wi4=0.63	P'(i+1)4=44	P''(i+1)4=25
Pi5=50	Wi5=0.63	P'(i+1)5=54	P''(i+1)5=28

Notes

Pi: generated parents in *i-th* iteration

P' i+1: generated parents in *(i+1)-th* iteration by using Triangular shape Functions (Type 1)

P''i+1: generated parents in *(i+1)-th* iteration by using Triangular shape Functions (Type 2)

Pi, P' i+1, P''i+1 are rounded decimal values equal with chromosomes' binary strings.

Table 3: Test problem specifications for solution procedures

Test Problems	a	tp	tp (l)	L	d	M	k	β
TP1	2	2	2	2	7	2	3	5 – 50
TP2	3	12	6	6	7	2	3	5 – 50
TP3	4	36	10	12	7	2	3	5 – 50

Tpi: the *i-th* Test Problem.

a: total number of airports

tp: total number of traveling programs(with 1 or 2 Flight Leg(s))

tp(l): number of traveling programs that contain each flight leg

L: number of all flight legs

d: number of all time blocks such as the days of week, month,....

M: maximum number of fare classes in CRS (CRS Capacity)

k: number of fare classes considered for itinerary i in selected price structure(Price Structure Capacity)

β: mean and scale parameter for exponential density function.

$$P_{(i+1)j} = \omega_{T_{ij}} \times P_{i1} + (1-\omega_{T_{ij}}) \times P_{i(j+1)} \tag{13}$$

In Table 2, Triangular shape Membership functions are applied to Fuzzy-Arithmetic Weighted Mean process in some numerical scenarios.

Computational Results: At first, we bring forward different scales Test Problems that their specifications, are summarized in Table 3. The number of binary variables (X_{ijk} & W_{im}) and equality & inequality constraints are compared in table 4, for each Test Problem.

We determine results in the viewpoint of calculation times and average profits for each problem. The effectiveness of introduced crossover operators has been examined by means of Test Problems.

CPU times are in seconds and have been calculated since the start of solution process. Numbers are average of ten independent simulations after 100 complete generations.

All procedures are simulated by a Laptop computer with an Intel Core 2 Duo 2.20 GHz processor.

Table 4: Different dimensions of the test problems

Test Problems	Number of W_{im}	Number of X_{ijk}	Equality constraints	Inequality constraints
TP1	6	300	2	8
TP2	36	1800	12	42
TP3	108	5400	36	120

Table 5: Classical genetic algorithm specifications

GA Parameters	Type or Quantity
Population Size	20
Selection Function	Uniform
Creation Function	Uniform
Elite Number	2
Mutation Function	Adaptive Feasible
Crossover Fraction	0.5
Crossover Function	Scattered
Generations	100

Table 6: Calculation times for crossover types (Problem 1)

Crossover Types	TP1	TP2	TP3
Scattered	1. 52	5.76	63.72
Single Point	1.64	5.94	59.57
Two Point	1.34	5.82	65.12
Intermediate	1.33	5.00	15.29
FAWM Bell) type : 1)	1.34	5.68	34.70
FAWM Bell) type : 2)	1.37	4.79	7.32
FAWM Tri) type : 1)	1.49	5.91	22.57
FAWM Tri) type : 2)	1.51	4.72	7.20

Table 7: Average profit for crossover types (Problem 1)

Crossover Types	TP1	TP2	TP3
Scattered	139.19	135.17	31.66
Single Point	142.05	150.00	9.12
Two Point	135.27	146.87	26.87
Intermediate	137.75	135.82	19.62
FAWM Bell) type : 1)	142.49	184.83	29.06
FAWM Bell) type : 2)	258.68	126.47	2.94
FAWM Tri) type : 1)	149.34	184.82	24.96
FAWM Tri) type : 2)	225.50	120.36	2.88

Table 8: Calculation times for crossover types (Problem 2)

Crossover Types	TP1	TP2	TP3
Scattered	1.44	5.08	9.70
Single Point	1.28	5.18	7.94
Two Point	1.33	4.76	9.62
Intermediate	1.51	4.42	10.46
FAWM Bell) type : 1)	1.30	4.68	7.75
FAWM Bell) type : 2)	1.54	5.84	38.25
FAWM Tri) type : 1)	1.34	6.01	15.32
FAWM Tri) type : 2)	1.46	6.57	20.99

Table 9: Average profit for crossover types (Problem 2)

Crossover Types	TP1	TP2	TP3
Scattered	232.89	158.26	5.88
Single Point	250.73	154.20	25.54
Two Point	246.50	151.41	16.99
Intermediate	229.95	82.18	10.97
FAWM Bell) type : 1)	234.38	117.98	21.85
FAWM Bell) type : 2)	159.43	159.87	16.20
FAWM Tri) type : 1)	258.05	129.96	27.35
FAWM Tri) type : 2)	163.11	185.47	24.38

Basic Genetic Algorithm that solution procedures started with, are specified in Table 5.

Tables 6 to 9 represent the calculation times and average profits for Problem1 and Problem2, respectively.

The following results are obtained with considering 3 of Best Solution Times and Average Profits between Crossover Types for each Test Problem.

Green ellipses show low Solution Times, Blue ellipses indicate high average Profits and the Red ones represent low Solution Times and high Average Profits in one case, simultaneously.

Problem 1: In above tables, not only fuzzy crossover methods enhanced the quality of solutions significantly in most cases, but also they had fairly good calculation times.

Repeating the fittest parent in all children, leads to great cancellation of GA random capability, in second and forth operators. As a result, solution ability of these methods was decreased. Then, less than our expectation, these methods could not have suitable solvability, especially for problem 2.

It is predictable that with reducing crossover rate and increasing mutation rate in the population of chromosomes, this deficiency can be easily compensated. In other words, algorithms with high degree of randomization return better resultants in solution process.

Membership Function Width Effect on Algorithm Quality

Bell Shape Functions: Figure 3 shows the effect of Bell shape width on the solution process speed and the solutions fitness value.

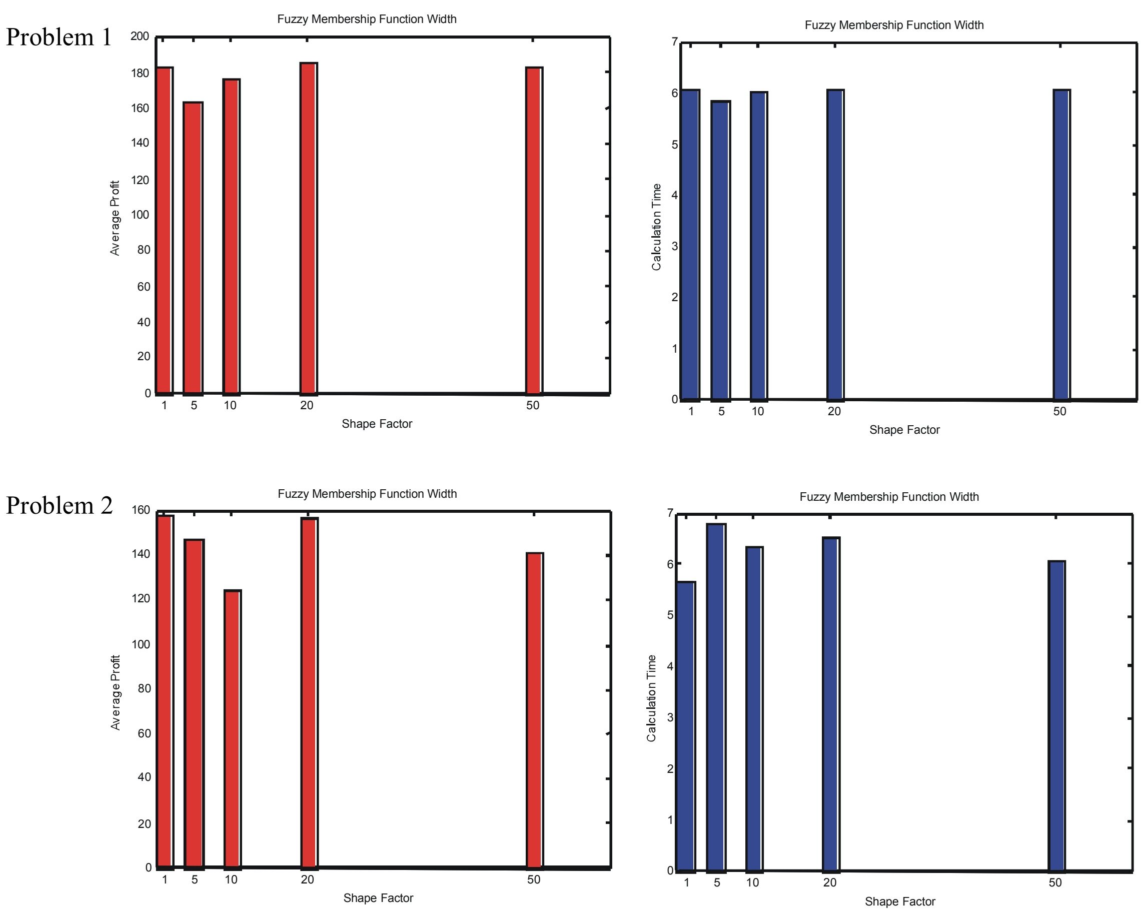

Fig. 3: Bell shape Function width effect on the calculation time and the quality of solutions

Problem 1

Problem 2

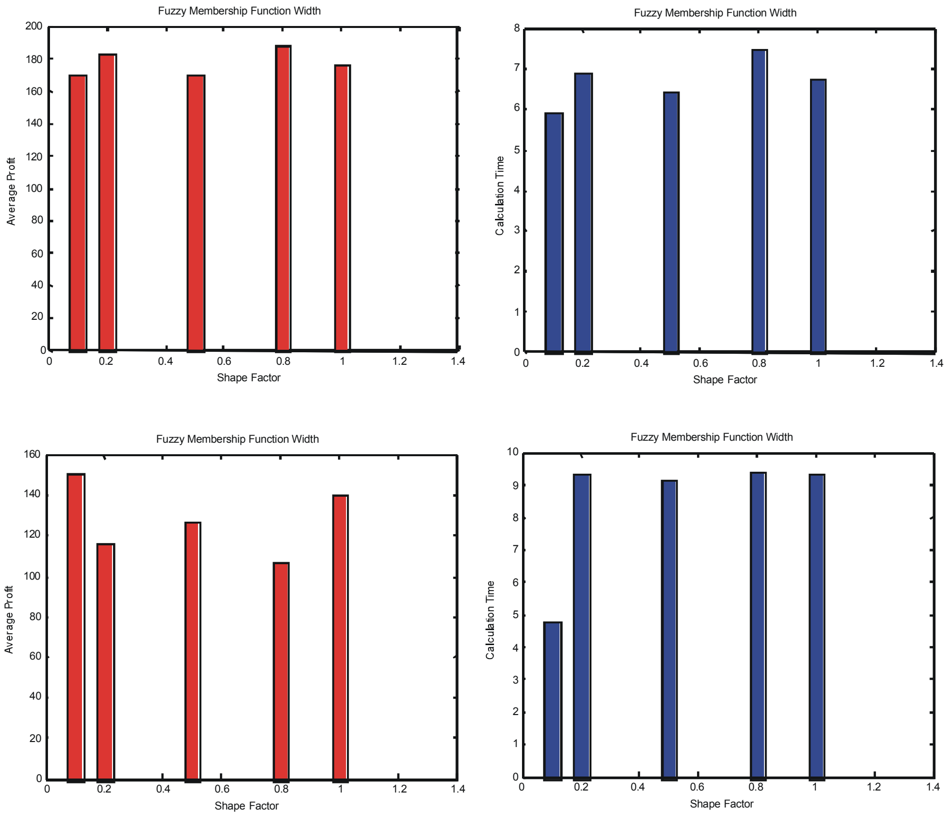

Fig. 4: Triangular Shape Function width effect on the calculation time and the quality of solutions

Calculation times were approximately fixed for different widths of membership functions. Algorithms were speeded up a little with increasing the width (decreasing the Shape Factor).

In most cases, the quality of returned solutions was increased using wider membership functions. Due to stochastic characteristic of GA, procedures were also encountered with exceptional cases.

In other words, algorithms were sent back fitter outputs by increasing Bell shape function width (closing to linear form (Triangular Shape)).

Triangular Functions: Figure 4 shows the effect of triangular shape width on the solution process speed and the solutions fitness value.

With narrowing triangular membership functions (decreasing the Shape Factor), calculation times closed to minimum value. On the other hand, average profits of Problem1 are nearly fixed values and even unbelievably, the average profit of Problem2 reaches to maximum values!

So, the narrower shapes are more appropriate in solving mentioned problems with GA, because of considering higher weights for fitter parents. However, exceptional cases also can occur with negligible probabilities. Hence, the linear weights are more suitable and consequently they have better performances.

CONCLUSION

In this paper, som new heuristic algorithms have been developed to solve efficiently Pricing & Seat allocation problem in airlines. These new methods use fuzzy membership functions to improve crossover operator in Genetic Algorithm. We also search to find the best width in Bell shape and Triangle shape Fuzzy Membership Functions.

Our simulations confirm that the widest Bell shape function and the narrowest Triangular one are the best selections for solving represented problems.

Two different problems are formulated. Reaching to Maximum Revenue is the object of cost function and system constraints such as Flight Leg Capacity, CRS Capacity, the number of defined fare classes and the other ones are also assumed in model definition.

- Each solution is a convex hull of BIP problems.

Finally, the following suggestions are recommended for future works:

- Using more completed models with other efficient parameters in pricing and seat allocation process such as Quality Level, Safety Level and Satisfactory Degree that is delineated for all airlines.
- Applying search methods that can contribute to speed up convergence of GAs such as Messy GA.
- Utilization of Hybrid Algorithms in solution process that are used to combine the abilities of classical and heuristic methods to return faster and overprecise outputs.

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